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ADA-CMM: A Capability Maturity Model for Advanced Data Analytics

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Abstract

Despite the rising importance of advanced data analytics, there is limited guidance on how organizations should leverage it. The benefits that an organization can gain through advanced data analytics depends on the organization's ability to gain and use relevant capabilities. This study introduces a capability maturity model (ADA-CMM) for advanced data analytics to help organizations assess their current state of capabilities for managing advanced data analytics. We used the Delphi method to develop the maturity model and performed a survey to evaluate its validity. The results confirm that the maturity level of the advanced data analytics capabilities of organizations is positively related to the business value that they can capture from their use, which in turn found positively related to organizational performance. ADA-CMM can be used by organizations as a self-assessment tool and to create a roadmap for improving their relevant capabilities.

1. Introduction

With the advancements in digitalization, more organizations employ advanced data analytics (ADA) to improve their processes, products, and services [1] and gain a competitive advantage [2]. ADA refers to the information systems and analytics applications used to collect, analyze, and extract insights from data to be used in organizational decision making and the development of product/service offerings [3]–[5]. Businesses can have improved performance with respect to their competitors by 5% in productivity and 6% in profitability when analytical techniques have been successfully applied [6]. Researchers have also claimed that big data analytics (BDA) will cause a revolution and transform the way we work, live, and think [4]. Despite the opportunities brought by implementing ADA, many organizations struggle to capture business value from their analytics initiatives [5], [7]. They face social, organizational, and technological challenges in adopting ADA and creating value from it [8]. Some key challenges include translating data into insightful knowledge, making data available in the right form at the right location, and adapting the business to changing data usage patterns [2], [9], [10]. It is expected that through 2022, only 20 percent of analytic insights will deliver business outcomes [11]. These analyses indicate a lack of awareness on the capabilities that organizations should possess to cope with the challenges of implementing ADA [8], [10]. Thus, they need guidance on developing organizational capabilities to implement ADA for business value creation [5] and harvest the benefits of increased organizational performance [12].

Maturity models are used to guide organizations in developing organizational capabilities [13]. They are conceptual models that indicate the level of maturity of the capabilities required for a specific process or class of processes in an organization. They represent an anticipated, desired, or typical evolutionary path for these processes [14].

There are a number of existing maturity models that propose a set of ADA capabilities that organizations need to acquire and use. However, these models are typically domain-specific, do not prescribe the necessary capabilities, nor have been empirically and rigorously validated [15], [16]. To address this critical gap, *we* have developed a *maturity model for advanced data analytics capabilities;* entitled *ADA-CMM*. ADA-CMM is a holistic, firm-level maturity model for organizations to assess their current state of ADA capabilities and develop a roadmap to improve their maturity level. It provides a descriptive tool for assessing the as-is ADA capabilities, which can also be used for prescriptive purposes to guide reaching higher maturity levels [17].

In developing the ADA-CMM, we have adopted a multi-method approach. First, we performed a literature review to identify the existing maturity models on ADA. Next, we designed an initial version of ADA-CMM

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based on the findings from the literature review. Through a Delphi study of three iterations with 9 field experts, the model was refined and finalized. Five ADA-CMM capabilities were identified: data & governance, performance & value, strategy, people & culture, process design & collaboration. Finally, we validated ADA-CMM by conducting a survey across multiple companies and evaluated our model. In this way, we investigated the relationships between the maturity of ADA capabilities, the value of ADA, and firm performance. The results indicate a significant positive impact of the maturity of ADA capabilities on firm's performance, mediated by the business value of ADA.

The remainder of this paper is structured as follows. First, our theoretical background section presents the existing data analytics maturity models and discusses the impact of ADA on firm performance. Second, we explain how our model, ADA-CMM, has been developed using the Delphi study. In Section 3, we describe the research process that we followed in developing the model. Section 4 presents the final version of the ADA-CMM. This is followed by its evaluation in Section 5. Finally, in Section 6, we conclude with the discussions on the implications of our study, its limitations, and future research directions.

2. Theoretical background

In this section, we first present a brief record of the existing maturity models on ADA and related concepts. Next, we discuss the key studies that investigate the influence of the ADA capabilities on firm performance.

2.1. Data analytics maturity models

A maturity model consists of a definition of an ordered set of maturity levels for processes in a business domain [18]. The anticipated, desired, or typical evolution path of these processes is described as increasing maturity levels. A maturity model can be used to assess the current situation, develop and prioritize improvements, and control the progress of the implementation [14]. In this sense, it may serve a descriptive purpose to understand the 'as-is' situation and a prescriptive purpose to guide the improvement of the current maturity level [19].

Many organizations have realized the importance of the opportunities ADA could generate. However, it is still a challenge to establish business processes that enable the value of ADA [20]. Organizations need guidance to execute ADA projects and implement ADA solutions [21]. A maturity model could provide a roadmap for organizations to improve their maturity level for their analytics capabilities [14].

We performed a literature review on maturity models originating from practice and research on ADA and related areas, e.g., big data analytics, business intelligence. We based our review on the two recent systematic literature reviews. The first one provides a comprehensive overview of the models specifically for big data and ADA [15]. The other study reviewed and comparatively analyzed the maturity models on 'analytics' [3]. These studies together identified 26 unique maturity models. Furthermore, through forward snowballing (following the technique in [22]) of the referred papers in these studies, we have identified 31 unique models in total [1]. Twenty-four of these originate from practice, and the remaining 6 have been published in the academic literature.

Among the practice-based maturity models, 4 of them are identified as the commonly-used ones [15]. The Analytics Maturity Model developed by The Data Warehousing Institute is a tool to assess a firm's big data analytics governance, organization, data management, analytics, and infrastructure in five maturity stages, with a chasm between stage 3 and 4 [23]. The Big Data Business Model Maturity Index assesses a BDA business model in five dimensions: Business monitoring, business insights, business optimization, data monetization, and business metamorphosis [24]. It applies prescriptive analytics to optimize key business processes. IDS MaturityScapes is a prescriptive model that assesses the organizational BDA capabilities on vision, data, technology, people, and processes, and provides guidance to progress along the maturity stages [25]. The prescriptive model BDMM [26] is a big data maturity model with 6 stages from 'in the dark' to 'optimize and extent'. It can be used to assess the current situation and the desired situation across eight different capabilities. These 4 models have been developed in the industry by technology vendors, professional educational institutes, or consulting companies. Thus, documentation on their unbiased development and validation is missing, which is a common weakness of maturity models developed by the industry [16].

Recently, researchers have also worked on developing maturity models explicitly on ADA. For example, the Big Data Maturity Model aims to helps organizations leverage big data and its value [16]. The model focuses on five general dimensions (strategy alignment, data, organization, governance, and information technology) and nine sub-dimensions. The model focuses specifically on the general business implications of big data technology, providing a high-level assessment of these aspects. The model development and design relied on second-hand data.

[1] The complete list is available at: https://bit.ly/3vnAkjH

Another research-based maturity model is the "Value-Based Big Data Maturity Model" proposed in [27]. It focuses on the data quality and argues that this is critical in gaining a competitive advantage. The model proposed by Dremel et al. follows a similar path and incorporates 34 generic capabilities necessary to leverage the potential of big data analytics [28]. The model was developed using input from consultants working for a single company. Furthermore, the results have not been empirically validated. Cosic et al. [29] proposes a business analytics capability model consisting of 16 capabilities grouped under 4 areas (governance, culture, technology, and people). Similar to the abovementioned models, an empirical evaluation of this model is lacking.

In summary, several maturity models for advanced data analytics and related domains have been proposed by researchers and practitioners. These models are often domain-specific or focus solely on specific topics (such as the data quality). Many of these models do not incorporate necessary capabilities, nor are subjected to rigorous validations. Some do not provide details regarding their application, making their use in practice difficult. Moreover, many of such models focus solely on technological capabilities, ignoring the factors regarding the organization and context.

2.2. ADA and Firm Performance

ADA can help firms understand the organization and its competitive environment better and be more agile in strategic decision-making [30]. When it is strategically and technically implemented in an organization, it can promote innovation in product/service offerings and improved business decisions [2], [10]. Thus, it can be a significant differentiator between high and low-performing firms [31]. However, improving ADA capabilities and thereby achieving higher firm performance is a formidable undertaking [32].

The impact of ADA capabilities on value creation and firm performance has attracted attention of many researchers [33]. Elia et al. [34] explores ADA's potential to contribute to value creation in various organizational dimensions, e.g., strategic value for competitive advantage, transactional value for operational efficiency, and transformational value for business innovation. However, the ability to create value from ADA is considered to have a relation to the maturity level of ADA capabilities [1], [35]. These capabilities are not only about the technical aspects of ADA solutions, but they also encompass strategic, process, people, and process aspects [3], [21].

The study by Huang et al. [36] indicates a direct influence of the value generated from ADA on firm performance, measured in two dimensions: operational and market performance. Firm performance is defined as the extent to which a firm generates superior performance with respect to its competitors [4]. Operational performance is about productivity, profit rate, return on investment, and sales revenue of an organization [36]. Market performance is on the ability of the firm to enter new markets and improve its position in existing ones [4].

In brief, the literature suggests an influence of the ADA capabilities on various aspects of organizational performance. Hence, a positive relation between the *maturity level* of ADA capabilities - as specified by a specific ADA maturity model- and the firm performance would provide evidence for the validity of that maturity model. We will adapt this view for the evaluation of the ADA-CMM that we propose in this study.

3. ADA-CMM Development

In this section, we briefly present the research process we have followed for the development of the ADA-CMM.

3.1. Initial model design

As the extant literature suggests a substantial number and type of ADA capabilities for organizations, we base our initial model on the capabilities proposed in the literature. More specifically, the capabilities proposed by Brinch et al. [8] provided the foundation of our model. We chose these capabilities as they are based on a thorough review of the literature on the capabilities in various domains, such as big data analytics, advanced data analytics, IT, and business process management. These capability areas are frequently identified in other data analytics maturity models[1] and their relevance has been validated through a case study [8]. The list identifies the following 6 capability areas: IT, process, performance, human, strategic, and organizational capabilities.

Although the study by Brinch et al. [8] provides definitions for ADA capability areas and related practices, it does not propose a maturity model for them; hence, does not incorporate any structure or mechanism to assess the maturity level of these capabilities in organizations. Therefore, we explicitly adopted a maturity level structure and accordingly defined maturity level characteristics for all ADA capabilities.

We adopted the maturity model structure of the Process and Enterprise Maturity Model (PEMM) [37] as it allows for self-assessment and considered easy to apply in practice [38]. PEMM is a descriptive maturity model, which could also be used for prescriptive purposes [13]. Moreover, it is a continuous model; that is, it is based on scoring different dimensions (capabilities) at different levels and weighing the individual scores [39].

For the initial version of the ADA-CMM, we aligned the ADA capabilities, as defined by Brinch et al. [8], with the structure of the PEMM. Accordingly, we incorporated 24 sub-elements (capabilities) categorized under 6 main elements (capability areas). Adopted from PEMM, each sub-element is characterized by 4 maturity levels. The structure of the ADA-CMM is depicted in Figure 1.

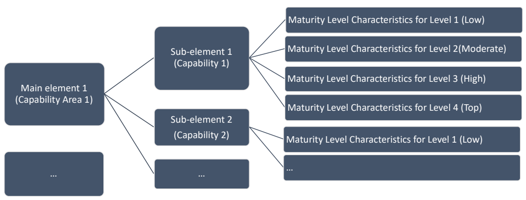

Figure 1. The structure of the ADA-CMM

3.2. Model refinement with the Delphi study

Delphi study is a method for structuring a group communication process. It is a method where a panel of experts evaluates the content of the developed artifact. It is executed in multiple rounds of questionnaires moderated by a facilitator [40]. The experts do not directly face each other to prevent bias. We chose this method because it provides the opportunity to access a broad range of domain experts and combine their views when there is a need to solve a practical problem [41].

The panelists were selected based on their experience and knowledge of the ADA domain. Potential experts were contacted via email. Among 15 experts that have been approached, 9 accepted the invitation to take part in the panel. It is important to have a heterogeneous group of experts in terms of their background, to reduce single culture bias and provide diverse insights [42]. The panelist included 3 academicians, 3 consultants, and 3 industry experts working in the ADA and related domains. Personal introduction meetings were conducted to ensure the engagement of the participants, in which the objectives of the study and responsibilities of the expert panel were explained.

An ideal Delphi study involves 2 or 3 rounds, as more rounds may result in a slower convergence among expert opinions [43]. We asked the experts to contribute in 3 rounds through online questionnaires. In the questionnaire, for each main element (capability area) and sub-element (capability), the experts were asked to choose among 3 options: stay, change, or go. In case participants chose the latter two options, they had to provide reasoning about their decision. In the Delphi rounds, we took percentage agreement as the measure of the level of consensus and set 80% as the threshold to decide whether the elements should stay [44]. If this was not the case, the element was changed or removed from the model and presented to the other panelists in the following round.

In *Delphi round 1*, we presented the participants the structure of the model, main and sub-elements, and their definitions. In this first round, the maturity levels for each element were not presented. Two main points of feedback we received were on specifying the scope and focusing the model on ADA more explicitly through updating various elements and sub-elements. We explicitly defined the scope of the model as big data and advanced analytics projects related to business processes, IT, and business analytics in organizations. Furthermore, various changes were introduced in the names, definitions, or sub-elements of five of the six elements.

In *Delphi round 2*, the participants received a report of changes in the initial model due to their feedback. They also received the revised model including this time the definitions of the maturity level characteristics for each sub-element (capability). The discussions led to several changes in all components of the model. This included name changes in the main elements, and various content related changes in sub-elements and corresponding maturity level characteristics.

In *Delphi round 3*, the goal was to evaluate the descriptions of the maturity levels and confirm the main elements, sub-elements and corresponding 4 maturity level characteristics for each maturity level. According to the feedback, the model has been updated and finalized. The final model as a result of round 3 was sent back to panelists to receive a final confirmation.

4. ADA-CMM (Final Model)

In this section, we briefly introduce the final version of the ADA-CMM. Table 1 presents an overview of the main elements and sub-elements of ADA-CMM. Each main element encompasses a set of sub-elements that represent a distinct capability.

The element *People & Culture* considers the knowledge and commitment of employees regarding ADA, the diversification of teams, and the adoption of analytical capabilities to improve business processes. The *Performance & Value* focuses on the performance metrics that show how ADA capabilities can turn data into value and innovation processes to develop best-in-class service operations. The *Strategy* includes capabilities related to the definition of ADA vision, mission, and objectives, and the linkage of ADA to IT and business process priorities. The *Data & Governance* relates to the data architecture, elimination of repetitive manual work, the linkage of IT systems and operational processes, data governance, and the available data analytics tools. Finally, the *Process Design &*

Collaboration emphasizes on the capabilities regarding the competence and skill development of employees, the way they are informed about new technologies, how ADA projects are managed, and the extent of information sharing and functional project involvement.

Table 1. ADA-CMM main and sub-elements

Main Element (Capability Area)	Sub-Element (Capability)
People & Culture	Knowledge Commitment Team Diversity Usage
Performance & Value	Performance Metrics Innovation Processes
Strategy	ADA Strategy Strategic Alignment
Data & Governance	Data Architecture Automation Data Integration Data Governance Data Analytics Tools
Process Design & Collaboration	Competence & Skills Development Communication Portfolio Management Organizational Collaboration

ADA-CMM further includes the definition of sub-elements and corresponding maturity level characteristics in 4 levels. There are 17 sub-elements related to a specific element, representing an organizational capability necessary to create value from ADA. We provide an excerpt of ADA-CMM as an example in Figure 2 and provide the complete model in the online report[2]. We built the descriptions of sub-elements based on the main sources we used for ADA capabilities ([8], [37]), and enriched them with other sources in the literature where possible.

Each sub-element is characterized by four maturity levels and related characteristics similar to PEMM [37] (low, moderate, high, and top levels). For each sub-element, an organization can be at a different level (as exemplified in Figure 2) and weigh the individual scores into an average maturity score per main element.

Organizations can use ADA-CMM to assess the current situation, develop and prioritize improvements, and control the progress of implementation [13]. It can be used as a self-assessment tool of the ADA capabilities. To gain a more reliable self-assessment, it is ideal that the assessment is conducted with multiple participants with different organizational roles, backgrounds and motivations [45]. The assessment can take place in a focus group or workshop setting where everyone can express their opinion and have a group discussion about each element until there is a consensus. Alternatively, it can be performed as an online survey, where every participant individually expresses their opinion, and the results are aggregated.

The self-assessment represents the current situation and unveils the areas of ADA capabilities in which the organization excels, and which areas have room for improvement. The gap between the current situation and the desired situation can help prioritize improvements in the ADA capabilities. Conducting a regular self-assessment can facilitate monitoring the progress of improvements. The target group of ADA-CMM is the organizations using or planning to implement ADA within their organization. Finally, the ADA-CMM can be used to benchmark and identify the organizational ADA performance compared to the industry standard.

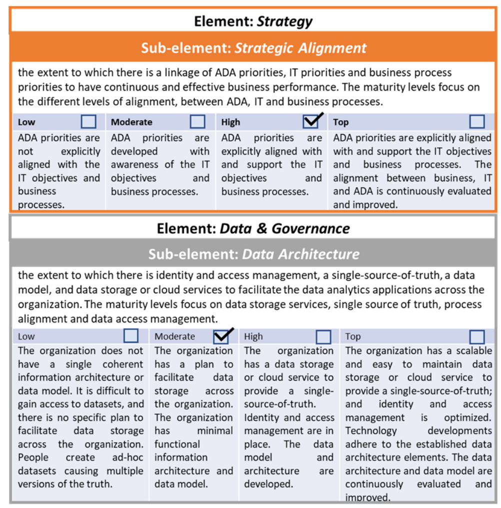

Figure 2. An excerpt from ADA-CMM, containing an example sub-element and maturity level characteristics for the Strategy and Data & Governance elements

5. Evaluation

Although ADA-CMM has been developed as a joint effort of domain experts through a Delphi study, it should be evaluated in real-life business settings. For its evaluation, we focused on its validity [13], i.e., that it can be used for its intended purpose of use. Accordingly, we proposed the research model depicted in Figure 3. We presumed that the maturity level of ADA capabilities of an organization impacts the firm performance through the value generation potential of ADA (ADA value) as a mediator. We expect a mediation effect as we presume that the increased firm performance can materialize only when ADA capabilities are put in action and value is generated from ADA initiatives.

[2] The complete ADA-CMM is available at: https://bit.ly/35qQIW6

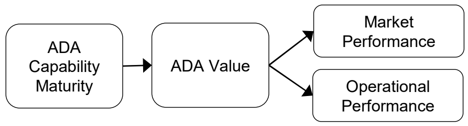

Figure 3. Research model

5.1. Evaluation Method

To evaluate the validity of ADA-CMM, we designed an online survey to collect data about the maturity level of ADA capabilities of organizations (as assessed using ADA-CMM), the value creation aptitude of ADA (ADA Value), and the firm performance (as characterized in 2 forms: market and operational performance).

The survey consisted of four sections[3]. The *first section* evaluated the maturity level of ADA capabilities of organizations as assessed by ADA-CMM. This section consisted of 17 questions, each referring to one of the sub-elements of ADA-CMM. The definitions of the sub-elements were rephrased such that they became a question. Each question had a 4-point Likert scale, ranging from 1 (to a small extent) to 4 (to a very great extent) corresponding to the 4 maturity levels and aligned with our maturity model structure [37].

The *second* part of the survey focused on the value creation aptitude of ADA in a firm. Based on the framework of Elia et al. [34], we defined five dimensions to measure the value created by ADA in an organization: informational, transactional, transformational, strategic, and infrastructural value. The statements had a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

The *third* part of the survey referred to the firm performance, which consisted of four items related to market performance and four related to the operational performance. These questions are based on the validated items as given in [4]. The statements had a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) and included an option of "don't know / not applicable".

The *final* part of the survey aimed at collecting general information about the survey participant and organization that is being assessed. The participants were asked questions on the country of their residence, age, work position, general work experience, and experience with ADA, and the sector and size of the organization. The name of the organization and participant were not mandatory fields for enabling anonymity if preferred. The answer options of the sector were classified using the GCIS scheme.

A pilot survey was sent out to several respondents to review the questions and completion time. The survey was distributed via social media and specifically targeted emails. The target group was information managers. The survey was online for three weeks, and the target group was actively stimulated to fill in the survey by sending out invitations and reminders.

5.2. Descriptives

In total 56 participants responded to the survey. We removed one response due to straight-lining and two responses due to missing data. Our univariate and multivariate outlier analysis did not result in the removal of any data. We aggregated multiple data points that correspond to participants from the same organization to reach a firm-level result. After data cleaning and aggregation, our data set consisted of 48 observations.

The descriptive information on the work and ADA experience of the participants and their organizational size are shown in Table 2. Participants were mostly from the sectors of industrials (e.g., capital goods, transportation) (29%), IT (26%), financials (14%), consumer staples (10%), and healthcare (7%). Figure 4 depicts the boxplots for the aggregated maturity scores per element of the ADA-CMM (D&G: Data & Governance, P&V: Performance & Value, S: Strategy, P&C: People & Culture, PD&C: Process Design & Collaboration), the overall score for ADA value, and the overall performance score aggregated for each organization.

Table 2. An overview of descriptive statistics

Personal experience (years)	**0**	**0-2**	**2-5**	**5-10**	**>10**
Work		28%	35%	24%	13%
ADA	17%	21%	24%	29%	9%
Organization size (employee #)	**<10**	**11-50**	**51-250**	**251-1000**	**>1000**
	7%	29%	19%	21%	24%

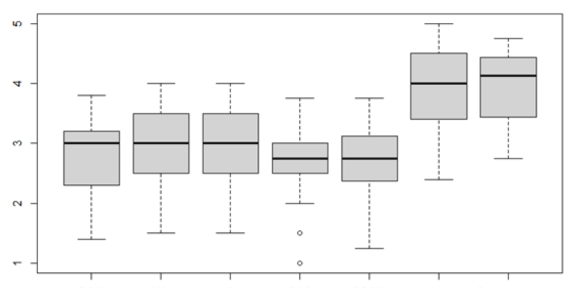

Figure 4. Box plots of the survey results per maturity level of ADA-CMM elements, ADA value, and firm performance of each organization

[3] The survey questionnaire is available at: https://bit.ly/2TxAyrg

5.3. PLS-SEM analysis

We used Partial Least Squares Structural Equation Modelling (PLS-SEM) analysis to test our research model depicted in Figure 3 with the survey data, and evaluate the impact of ADA-CMM capabilities on firm performance through “ADA value”. We defined ADA capability maturity level (shortly ADA maturity) as a second-order construct and used the five elements of ADA-CMM as formative indicators (i.e., first-order constructs) of the ADA capability maturity since the complete set of elements reflects this higher-order latent variable [46]. Each first-order latent variable was measured through indicators matching its sub-elements, e.g., Data & Governance with five indicators (coded as D&G_1 to D&G5). Similarly, the five items of ADA value were modeled as formative indicators and the items for the market and operational performance as reflective indicators.

Following the guidelines for conducting PLS-SEM analysis [47], we first checked the validity and reliability of the reflective measurement model. Next, as measures of fit for the reflective measurement models, we assessed the internal consistency reliability through Cronbach's Alpha (α) and composite reliability (CR), and convergent validity through Average Variance Extracted (AVE), as reported in Table 3. We assessed the discriminant validity through Heterotrait-Monotrait Ratio (HTMT), which resulted a value below 1.0. We confirmed that all these variables match the suggested threshold values and, thus, the indicators of the reflective model are of sufficient quality [47].

Table 3. Reliability and validity of reflective constructs

Construct	α	CR	AVE
ADA Maturity	0.912	0.924	0.422
Market Performance	0.651	0.792	0.489
Operational Performance	0.848	0.897	0.687

For validating the formative model, first, we confirmed the lack of multicollinearity issues in the outer model by checking the outer VIF scores, which were below the threshold of 5. To check the significance of the indicators, bootstrapping was performed with a sample size of 5000 [48]. An assessment of the outer weights revealed that all indicators were significant (p<0.05), except for D&G_1, S_1, P&C_2, P&C_4, PD&C_3, IMV, TCV, TFV. The outer loadings of these indicators were all above 0.5. Thus, we decided to retain as suggested [49]. We further confirmed that there are no multicollinearity issues for the structural model by checking the inner VIF scores to be 5 or more [49].

5.4. Results

The pathway coefficients for each relation are presented in Table 4. All relationships between the latent constructs are found significant (p<0.001). Each ADA-CMM element is shown to have positive influence on the ADA capability maturity level. The latent variable that influences maturity the strongest is 'Data & Governance' followed by 'Process Design & Collaboration'. 'Strategy' has the weakest influence on the overall ADA maturity. ADA maturity as a construct has, in turn, a strong positive influence on ADA value. The ADA value construct almost equally influences market performance and operational performance.

Table 4. Pathway coefficients of model relationships * denotes p<0.001

Relationship	Pathway coefficient
Data & Governance -> ADA Maturity	0.370*
Process Design & Collaboration -> ADA Maturity	0.272*
People & Culture -> ADA Maturity	0.260*
Performance & Value -> ADA Maturity	0.182*
Strategy -> ADA Maturity	0.121*
ADA Maturity -> ADA Value	0.645*
ADA Value -> Market Performance	0.685*
ADA Value -> Operational Performance	0.643*

The measures of structural model fit are presented in Table 5. The adjusted R^2 values of 0.400 to 0.458 indicate a moderate level of variance explained for dependent variables ADA value, market performance, and operational performance [48]. The Q^2 values, which indicate the model's predictive relevance, are all above 0. Thus, the model can be considered to have medium to high predictive relevance [49].

Table 5. Model fit values per construct

Construct	R^2	R^2 adjusted	Q^2
Value	0.416	0.403	0.236
Market Performance	0.470	0.458	0.193
Operational Performance	0.413	0.400	0.258

5.4. Discussion of the results

The significant positive relationships found between ADA-CMM elements and ADA maturity indicate that ADA capabilities in organizations impact the overall ADA maturity. The results contribute to the findings by [8], who provided a holistic overview of firm-level capabilities that are required for big data value creation, which served as the basis of the ADA-CMM. Our study redefined these capabilities in the context of ADA and independent of a domain, and empirically validated them. We contribute further by showing the diverse impact of capabilities on ADA value.

Our results show a significant positive relationship between ADA maturity and ADA value, indicating that a higher ADA maturity positively influences the value generated from ADA projects, measured in terms of informational, transactional, transformational, strategic, and infrastructural value. The results extend the findings of [34] by explaining the impact of ADA maturity on generating ADA value.

Finally, our results contribute to the literature on ADA performance. The results support that the value generated from ADA projects positively influences the market performance in terms of sales revenue, entering new markets, developing new products, and the success rate of new products. Furthermore, more value generated from ADA projects positively influences the operational performance in terms of productivity, profit rate, return on investment, and sales revenue. Our findings suggest that ADA maturity has a significant effect on firm performance indirectly via ADA value, which confirms the findings of [4].

6. Conclusion and Implications

In this paper, we proposed a capability maturity model for ADA. To develop the initial model, we synthesized the core elements of the capabilities identified at [8]. Then, the model was revised and refiled in a Delphi study of three rounds with nine domain experts, resulting in the artifact of advanced data analytics capability maturity model (ADA-CMM).

The validity evaluation of the ADA-CMM consisted of an analysis of the relationship between ADA maturity level and firm performance through a survey. The validation method provided insights into whether improving ADA maturity of organizations using ADA-CMM would lead to the generation of diverse organizational values, which in turn lead to higher firm performance. The survey data was collected from 48 organizations and analyzed using PLS-SEM. The results indicate that the maturity level of ADA capabilities included in the ADA-CMM has a significant positive impact on the ADA value creation aptitude. Finally, a significant positive relationship was found between ADA value creation aptitude and the organization's market performance and operational performance. Overall, ADA maturity was found to have a significant indirect effect on firm performance via ADA value.

6.1. Theoretical implications

This research contributes to the literature on advanced data analytics in several ways. First, it responds to the demand for an empirically validated maturity model that assists organizations to tackle the social, organizational, and technological challenges in adopting and creating value from ADA [7], [8]. To fill this gap, this study provides a holistic maturity model, which prescribes the necessary capabilities to create value from ADA and provides a roadmap for firms to improve their maturity level related to their advanced data analytics capabilities. The model differentiates itself from the existing maturity models in the way it has been developed and evaluated for its validity. It is developed by integrating the expertise of nine panelists including academicians, consultants, and industry experts through the Delphi study and further empirically evaluated through a survey involving 48 practitioners.

Second, this study contributes to the ADA literature by revealing the relationship between the organizational ADA capabilities, ADA maturity, ADA value, and organizational performance. Current literature has mostly looked into these relationships separately and has not quantitatively confirmed them (e.g., [4], [8], [34]. Our study helps to understand the importance of diverse ADA capabilities on organizational performance.

6.2. Practical implications

This research has several practical implications for practitioners, such as executives, data analytics managers, and other relevant employees. The findings highlight the importance of five capabilities in ADA value creation: data & governance, performance & value, strategy, people & culture, process design, and collaboration. The study attempts to create awareness among practitioners that gaining a competitive advantage from ADA is not possible by only collecting large amounts of data and putting in place advanced technologies. Among others, it is also about positioning ADA strategically, having the right people and culture with a good collaboration environment together with performance and value management processes.

ADA-CMM, as a descriptive maturity model, is a tool that can be used by organizations to assess their current situation, develop and prioritize improvements, and control the progress of their implementations [13], [14]. Organizations can use ADA-CMM to self-assess the maturity of their current ADA capabilities and unveil the ADA capabilities that the organization excels, and areas that have room for improvement. Assessment results provide input to develop a roadmap for improving their maturity level of the specific ADA capabilities. Conducting a regular self-assessment of the ADA capabilities can facilitate monitoring the progress of improvements. Finally, ADA-CMM can be used to benchmark and identify the organizational ADA performance compared to industry standards. Companies use maturity models to deal with business problems through ADA in a variety of industries ranging from manufacturing to services, education, and healthcare [50], [51].

6.3. Limitations and Future Work

Our study is subject to several limitations and has various potential directions for future work. First, ADA-CMM should not be considered a universal model with an exhaustive list of firm-level capabilities leading to ADA value. The proposed model and its capabilities should continue to evolve. Future research that would apply and further validate ADA-CMM in specific contexts and domains is required. This study can be extended by accommodating unique characteristics of such specific contexts.

Second, in our survey, we primarily relied on the responses of participants from one organization and some participants with no ADA experience. This poses risks to the internal validity of the research method, as maturity assessment requires viewpoints of multiple participants with different backgrounds and motivations [13]. For future research, it would be valuable to have multiple participants per organization to capture the diverse perspectives of organizational roles. Furthermore, with a bigger sample size, the control variables such as work and ADA experience, organization size, and sector should be analyzed to confirm the robustness of the impact of ADA value on organizational performance.

We have evaluated the ADA-CMM for its validity, i.e., whether increasing the maturity level of ADA capabilities -as defined by the ADA-CMM- would lead to the creation of value, and eventually increased firm performance. Future research should consider evaluating the model against other criteria, such as usefulness, utility, quality, or efficacy [52] and using objective performance measures such as revenue [12]. Evaluating the long-term impact of using ADA-CMM by a longitudinal study can also provide valuable insights since organizations struggle to justify the long-term benefits of ADA investments [10], [30].

Other future research directions include investigating the impact of capabilities and finding the reason behind the diverse impact. The importance of the capabilities can be further compared through analysis such as Importance-Performance Map Analysis (IPMA). These can help organizations prioritize their efforts in improving their maturity for different capabilities. Further, control variables can be analyzed, for example, industry or organizational size, to reveal the impact of ADA capabilities specifically in different contexts.

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